Journal of Economic Analysis 2023 2(4) 82-97

Journal of Economic Analysis

Homepage: https://www.anserpress.org/journal/jea

Probability of Achieving NDC and Implications for Climate Policy: CO-STIRPAT Approach

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ABSTRACT

This paper presents an analytical framework to assess the probability of achieving nationally determined contributions (NDC). The prediction model based on the Kaya identity is used to simulate the pathway of carbon emission until the target year. Applying the modified STIRPAT framework (named CO-STIRPAT) to data observed in South Korea shows that the probability that the predicted pathway with existing climate technology will stay above the NDC target pathway is significantly high. The result suggests that it is necessary to design a climate policy to improve energy intensity and carbon intensity by accelerating the advance in climate technology.

KEYWORDS

Climate policy; climate technology; climate finance; NDC; probability of achieving the NDC target; IPAT; ImPACT; STIRPAT; CO-STIRPAT; carbon emission; energy efficiency; carbon intensity; Kaya identity

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ISSN 2811-0943
doi: 10.58567/jea02040005
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Received 31 May 2023, Accepted 17 June 2023, Available online 21 June 2023, Version of Record 15 December 2023

1. Introduction

Under the Paris Agreement, each country has committed to the NDC (nationally determined contributions) target. Achieving these NDC targets is crucial since the Paris Agreement represents a global commitment to collective action to reduce emissions and limit global warming. If countries fail to meet their NDC targets, it could undermine the credibility of the agreement and weaken the collective effort to address climate change. Using a fully statistically based probabilistic framework, the probabilities of meeting their nationally determined contributions for the largest emitters are low (Liu and Raftery 2021). According to their results, the probability of staying below 2 °C of warming is only 5% on current trends. But if all countries meet their NDCs and continue to reduce emissions at the same rate after 2030, it rises to 26%. Also, when failing to achieve the NDC targets, each country may lose an opportunity to create new economic opportunities. For example, transitioning to renewable energy and improving energy efficiency can create new jobs and reduce energy costs in the long run. Thus, assessing how probable achieving the NDC targets is essential for making a realistic plan for carbon neutral pathway of economic development.

This paper aims to provide a concise framework to assess the probability of achieving the NDC target. The probability can be affected not solely by the current state of emissions, but also by the ambition gap, the implementation gap, and the political will of the countries involved. The ambition gap regarding the level of ambition of the NDC targets is concerning the carbon budget implied by the 1.5° or 2.0°C corridor set by the Paris Agreement (Friedlingstein et al. 2022). The level of ambition of the NDC targets varies greatly among countries, with some countries setting more ambitious targets than others. Countries that have set more ambitious targets may have a harder time achieving them. Höhne et al. (2018) review a variety of approaches to assess the ambition of the GHG emission reduction proposals by countries. They suggest assessing the ambition of the national climate proposals is particularly important as the Paris Agreement asks for regular reviews of national contributions. As for the implementation gap which refers to the difference between implemented policies and NDCs, the jurisdiction's targeted reduction path may be different from the actual and projected reductions achieved with the current set of climate policy instruments (Perino et al. 2022). The probability of our interest depends on the implementation plan and policies that promote clean energy, energy efficiency, and the reduction of carbon emissions. Furthermore, the political will of the countries involved is essential for achieving the NDC targets. We aim to design the framework as parsimoniously as possible by focusing on essential factors.

Evaluating the probability of achieving NDC targets could provide valuable insights into the effectiveness, ambition, and feasibility of current climate policies and measures. First of all, it can provide insights into the effectiveness of current policies and measures aimed at reducing greenhouse gas emissions. By analyzing the likelihood of achieving NDC targets, policymakers can identify the areas where more effort and resources are needed to increase the probability of success. The result of this paper could inform policymakers and guide them in developing more effective climate policies and measures. In addition, this study can help to assess the ambition of NDC targets. By comparing the predicted pathway feasible with the current climate technology to the NDC target pathway, the general public can evaluate whether the targets are ambitious enough to meet the goals of the Paris Agreement. Furthermore, the study can contribute to the broader debate on the feasibility of achieving global climate goals. By analyzing the probability of achieving NDC targets across different countries and regions, researchers can identify the challenges and opportunities for international cooperation and coordination in tackling climate change. This can inform discussions on the need for more ambitious and coordinated global action to address the climate crisis.

The paper proceeds as follows. First, we review the relevant literature and introduce our analytical framework. Next, we describe the design for empirical analysis and present the data. Then the paper provides empirical results resulting from applying the framework to the Korean NDC target. We finalize the article by presenting concluding remarks and directions for future research.

2. Literature review

Several studies have assessed if countries are on track to fulfill their NDCs as promised in the Paris Agreement. den Elzen et al. (2019) analyzes whether the G20 economies are on track to meet their NDC targets. They conclude that some economies are on track to meet their NDCs after evaluating the current policies of the G20 economies across scenarios. Dong et al. (2018) predict the probabilities of achieving the carbon emission targets set by INDCs of the top ten CO2 emitters based on their emission trends over the 1991–2015 period. According to different trends of economic growth, energy consumption, and changes in the share of renewable energy, the results show that there will be a shortfall in achieving targets by seven countries. Liobikienė and Butkus (2017) reveal the possibilities of EU countries to achieve the Europe 2020 strategy and Paris Agreement targets. They conclude that the EU countries should attempt more to reduce energy consumption and to increase the share of RES seeking to implement the target of GHG emissions committed in the Paris Agreement. Liu and Raftery (2021) develop a fully statistically based probabilistic framework. They find that the probabilities of meeting their nationally determined contributions for the largest emitters are low. Peters et al. (2017) develop a nested structure of key indicators to track progress towards the Paris goal, inform the five-yearly global stocktaking, and increase the ambition of NDCs. They show that many key indicators are currently broadly consistent with emission scenarios that keep temperatures below 2°C. Roelfsema et al. (2020) conduct a similar analysis from the perspective of the emissions budget. They find that the countries evaluated are found to not achieve their pledged contributions with implemented policies (implementation gap) or to have an ambition gap with optimal pathways towards well below 2 °C.

There have been various studies analyzing the feasibility of achieving the Paris Agreement goals based on the NDCs submitted by countries. Bauer et al. (2017) estimate the feasibility of achieving those goals with a modeling framework to identify the socioeconomic conditions required. Grubler et al. (2018) estimate the likelihood of achieving this scenario based on the NDCs submitted by countries for a scenario for achieving the 1.5°C temperature target and the sustainable development goals without relying on negative emission technologies. Rogelj et al. (2016) estimate the likelihood of achieving the temperature goals, being based on an analysis of the aggregated impact of the NDCs submitted by 190 countries in the context of the Paris Agreement.

Many studies have used the IPAT identity, the ImPACT identity (as a widely recognized instance, the Kaya identity), and the STIRPAT framework for analyzing the key drivers of carbon emissions. Ang and Zhang (2000) use the Kaya identity, combined with index decomposition analysis (IDA). They conclude that the methodology helps quantitatively analyze the impact of interest on aggregate indicators, such as the intensity or total amount of carbon emissions. Hwang et al. (2020) analyze the causal relationships between the individual Kaya identity factors to identify the real and relevant drivers of carbon emissions. They find out that the indirect effects of the decomposed variables on the carbon emission are significant. Jin and Kim (2017) use the Kaya identity to present the necessity of having sufficient finances to implement measures contained within NDC. They estimate the cost associated with implementing an emission-reducing policy by setting the link between emissions and the government budget balance. Raftery et al. (2017) develop a statistically-based probabilistic forecast of carbon emissions by using a country-specific version of Kaya's identity. They point out that achieving the goal of less than 1.5°C warming will require carbon intensity to decline much faster than in the recent past. Wang et al. (2021) estimate EKC (Environment Kuznets Curve) for 198 countries between 1990 and 2018, within the STIRPAT perspective. Utilizing the quadratic function specification, they confirm robust U-shaped EKC and categorize sample countries in terms of sustainable or non-sustainable concerning average affluence. York, Rosa, and Dietz (2003) assess the analytic utility of the IPAT identity, the ImPACT identity, and their stochastic version, the STIRPAT model. They conclude that the STIRPAT model allows for a more precise specification of the sensitivity of environmental impacts to the forces driving them when the model is augmented with measures of ecological elasticity.

Some academic papers explore the relationship between carbon emissions and various socioeconomic drivers. Le Quéré et al. (2019) analyze the drivers of decreasing CO2 emissions in a group of 18 developed economies that have decarbonized over the period 2005–2015. It is found that countries need to enhance efforts to reduce emissions by more stringent policy actions to support a global peak in emissions in line with the goals of the Paris Agreement. Li et al. (2023) analyze the temporal evolution trend of carbon emissions of key industries in Beijing. Their results show a negative impact on carbon emissions from the number of permanent residents and urban green space areas whereas a positive impact on carbon emissions from energy consumption intensity, GDP per capita, and the ownership of civil cars. Perino et al. (2022) identify an implementation gap in the sense that the current climate policy mix is not sufficient to reach these targets. They conclude by pointing towards conditions for closing the implementation gap by discussing the potential effectiveness of prominent drivers of climate-related regulation in overcoming obstacles. Zhao et al. (2023) study the situation of machine learning applied to carbon emission prediction. They find that the carbon emission prediction models are based on five types of models(back propagation neural networks, support vector machines, long short-term memory neural networks, random forests, and extreme learning machines).

3. Analytical Framework for predicting carbon emission

3.1. Kaya identity

We assume that the Kaya identity is an adequate description of reality. The Kaya identity describes the factors that contribute to carbon emissions (Kaya and Yokobori 1997). It states that the total carbon emissions of a country can be expressed as the product of four factors: population, GDP per capita, energy intensity, and carbon intensity.

$$C = \frac{C}{E} \times \frac{E}{G} \times \frac{G}{P} \times P \equiv CE \times EG \times GP \times P \tag{1}$$

where C is carbon emissions, E is energy consumption, G is GDP, and P is population. Here is a brief explanation of each of these factors. Population (P) refers to the total number of people in a given country or region. The more people there are, the more carbon emissions are likely to be produced. GDP per capita (GP) is a measure of the economic output of a country or region, divided by its population. Countries with higher GDP per capita tend to have higher carbon emissions, as they have more resources to use for energy production and transportation. Energy intensity (EG) measures the amount of energy needed to produce a given level of economic output. Countries with higher energy intensity tend to have higher carbon emissions, as they require more energy to produce the same amount of goods and services. Carbon intensity (CE) measures the amount of carbon emissions produced per unit of energy used. Countries with higher carbon intensity tend to have higher carbon emissions, as they use energy sources that produce more carbon dioxide, such as coal.

The variables from the Kaya equation look more like consistent indicators actionable under the right choice of policies. Overall, using indicators from the Kaya identity seems to be a good choice to assess efforts made by a country or region concerning carbon emissions. Once we identify the factors that contribute to carbon emissions, we can develop strategies to reduce them. For example, increasing the use of renewable energy sources or improving energy efficiency can lower the energy and carbon intensity factors, ultimately reducing overall emissions.

3.2. Theoretical basis

The theoretical basis of this paper is a commonly used framework in the field of sustainability studies to understand the drivers and impacts of economic activities on carbon emission: IPAT, ImPACT, and STIRPAT. These theoretical concepts are often used as a starting point for discussions on sustainability and to understand the complex interactions between human activities and the environment.

As discussed in early papers (Commoner 1971; Ehrlich and Holdren 1972), IPAT (Impact, Population, Affluence, and Technology) is a simple equation that expresses the environmental impact (I) as the product of population (P), affluence (A), and technology (T). The identity highlights the multiplicative relationship between these factors and their combined influence on environmental impacts. IPAT emphasizes the role of population growth, increasing affluence patterns, and technological advancements in shaping environmental degradation.

As an extended IPAT framework reconceptualized by (Waggoner and Ausubel 2002), ImPACT (Integrated Model of Population, Affluence, Consumption, and Technology) includes an additional factor: consumption (C). The concept recognizes that the environmental impact of human activities is determined by the level and patterns of consumption as well as population size, affluence, and technology. ImPACT focuses on the interconnections between population dynamics, economic development, consumption patterns, technological choices, and their combined impacts on the environment.

As a statistical version of IPAT reconstructed from related research (Dietz and Rosa 1994; Rosa and Dietz 1998), STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) seeks to explain environmental impacts by examining the relationship between population, affluence, technology, and environmental factors. Based on the assumption that environmental impacts are driven by those factors, STIRPAT uses regression analysis to estimate the influence of these variables on environmental outcomes. The model often includes various human activities, such as urbanization, industrialization, and resource consumption. The three frameworks differ in terms of their complexity and the variables they consider although they share a common focus on understanding the relationship between human activities and environmental impacts.

Our approach is based on ImPACT in the sense that it utilizes the Kaya identity to examine the multiplicative influence of population, affluence, consumption, and technology on environmental impacts. Also, we propose a statistical model in the same line of STIRPAT although the statistical formulation is different from the conventional STIRPAT. Given these similarities and differences, we name the framework CO-STIRPAT (Component-Oriented STIRPAT).

3.3. Predicting components of ImPACT

We use the logistic function to predict the future pathway for individual components of ImPACT identity. Utilizing the logistic function (also known as the sigmoid function), our framework has the following form:

$$C_t = \prod_{i \in I} X_{i,t} \tag{2}$$

$$X_{i,t} = \beta_{i,0} / \left(1 + exp\left[-\beta_{i,1}\left(t - \beta_{i,2}\right)\right]\right) + \varepsilon_{i,t} \tag{3}$$

$$\varepsilon_{i,t} \sim N\left(\mu_i, \sigma_i^2\right) \tag{4}$$

where X_i is an element of the set of Kaya identity components, $I = \{P, GP, EG, CE\}$, and t is a time variable (year). The function maps a real-valued number to a value between 0 and $\beta_{i,0}$, the upper asymptote. $\beta_{i,1}$ represents the slope around the inflection point, and we can use it to control the growth behavior. If $\beta_{i,1} < 0$, then $X_{i,t}$ increases over time and if $\beta_{i,1} > 0$ then $X_{i,t}$ decreases over time. $\beta_{i,2}$ controls the location of the inflection point (relative to t), and thus the function has an S-shaped curve with an inflection point at $t = \beta_{i,2}$. This property makes the logistic function useful for predicting the pathway of trend-stationary variable, as it ensures that the predicted values are bounded between 0 and $\beta_{i,0}$.

Our analytical framework has some differences from conventional STIRPAT models. First, we can directly estimate the technology (T) in our approach. As pointed out in (York, Rosa, and Dietz 2003), it is conventional that T represents everything that is not population and affluence. T is solved to balance I, P, and A in the IPAT identity. This is included in the error term rather than estimated separately, in the typical application of the basic STIRPAT model. The approach to capturing everything else in the residual term is used to avoid the multi-collinearity issue that independent variables in a regression model have a high. Second, our methodology allows for the possibility that the future pathway of each factor may be non-linear. For studies that have sought to identify nonlinear relationships, such as the environmental Kuznets curve, the inclusion of quadratic or other polynomial terms in the regression model has been used. In comparison, we keep the relationship between carbon emissions and other factors in ImPACT but assume a non-linearity in the dynamic pathway of each factor. Third, our model incorporates stochastic factors into the dynamic pathways of each factor instead of keeping ImPACT as an accounting relationship. This approach allows for a richer design of the impact of changes in climate policy and climate technology on the future dynamics of each factor. Given these similarities and differences, we name the framework CO-STIRPAT (Component-Oriented STIRPAT).

3.4. Distribution of predicted carbon emissions

Since we conduct our analysis in the context of nonlinear regression, the delta method is used to approximate the distribution of predicted carbon emissions that result from a function of four components. The procedure used to derive a prediction band for the response variable (carbon emission) at a given set of predictor values (four components) is as follows. First, we fit the nonlinear regression model for logistic functions to the data and obtain estimates of the regression coefficients and their variances. After that, we choose a set of predictor values, $x_0 = [\widehat{CE}_t, \widehat{EG}_t, \widehat{GP}_t, \hat{P}_t]$, at which we want to predict the response variable. Then, we calculate the predicted value of the carbon emission, $y_0 = \hat{C}_t$, at x_0 using our fitted regression model. Next, we calculate the gradient vector of the regression function concerning the regression coefficients at x_0, the Jacobian matrix J_0. Next, we calculate the variance-covariance matrix of the components, V. Following the convention of the delta method, we approximate the distribution of the difference between the predicted value of the response variable and its true value at x_0. The mean of this distribution is y_0. The variance of this distribution is approximately $(J_0 \times V \times J_0')$.

From this distribution, we calculate a prediction band for the carbon emission at x_0 with a given level of confidence. For example, a 95% prediction band would be the mean plus/minus 1.96 times the standard deviation of the distribution from the previous step. Note that the delta method is an approximation and may not be accurate in all cases, particularly if the nonlinear regression function is highly nonlinear or if the sample size is small.[1]

3.5. Required improvement of climate technology

Our analysis first addresses the question of whether the NDC pathway lies within the prediction band associated with the forecast value of carbon emissions. The probability of achieving the NDC target depends on technological progress as well as the overall economic condition. The empirical research can provide a clue to an interesting question of whether the NDC target is compatible with the existing technology.

Another important question to be considered is how the gap against the NDC target can be decreased. Referring to the discussions within IPAT, ImPACT, and STIRPAT (York, Rosa, and Dietz 2003), the solution to the question is the enhancement of energy efficiency and carbon intensity, powered by adopting new climate technologies. Climate technologies are designed to reduce carbon emissions by enhancing energy efficiency and promoting renewable

[1] In such cases, other methods such as Monte Carlo simulation or bootstrap resampling may be more appropriate.

energy sources. To achieve their NDC targets, countries require investments in R&D and large-scale deployment of climate technologies. Our CO-STIRPAT enables us to quantify the required improvement of climate technology to meet the NDC target, regarding carbon intensity and energy intensity. For an illustration of applying our framework in practice, we adopt the NDC target pathway that the Korean government has announced recently. The target pathway is compared with the predicted pathway from the previous step, which has been derived by combining projected pathways of elements. Then, the required emissions reduction is identified by subtracting the NDC target pathway from the predicted level of emissions.

In the longer term, climate technology and climate policy can be synergistic if they are well-designed. Climate policy and technology are interconnected and mutually influential in many senses. Both start with the recognition of the problem of climate change, the urgent need to mitigate carbon emissions, and the adaption to changing climate conditions. Climate policy can play a pivotal role in supporting the development and deployment of climate technologies. Climate technologies are instrumental in achieving the objectives set by climate policies. Considering this iterative and dynamic relationship between them, it is important to identify policy priorities that control the direction of technology development and adoption. Policy adjustments and revisions may be necessary as a scientific understanding of the relative costs between energy efficiency and carbon intensity evolves. Thus, it is essential to ensure cost-effective climate policies by making the appropriate combination between energy efficiency and carbon intensity. Our CO-STIRPAT framework can be used to provide relevant information to do this task.

4. Empirical Analysis

We follow three steps: identifying the future pathway of components of the Kaya identity, estimating the distribution moments of carbon emissions, and comparing the projected pathway of carbon emission and the NDC pathway.

4.1. Data

Our dataset comprises population, GDP, energy consumption, and carbon emission. We obtain their annual data for 43 years (1980-2022) from the ECOS system of the Bank of Korea and the KOSIS system of Statistics Korea. Figure 1 shows the observed values and fitted values for each element of the Kaya identity: carbon intensity (CE), energy intensity (EG), GDP per capita (GP), and population (P). The shape of the curve is determined by the coefficients of the non-linear regression, and the fitted line represents the relationship between time and the level of the element of interest. We use these fitted lines to make predictions about the pathway of the elements during upcoming years until 2030, the target year of NDC.

The curve for population and GDP per capita starts at a low level for early years and increases over time, approaching its upper asymptote $\beta_{i,0}$ for recent years. For GP and P, the curve has transitioned through the inflection point, the year where the fitted line is steepest. The decreasing slope of the fitted line in recent years represents the declining growth rate at which the element changes as time passes. It shows that the upward trend of population and GDP per capita are weakening. In contrast, the curve for carbon intensity and energy intensity starts at its upper asymptote $\beta_{i,0}$ for early years, and declines over time, approaching a low level for recent years. Around the year 2018 when the carbon emissions in Korea peaked, the slope of the curve indicates the speed at which carbon intensity and energy intensity improve through the adoption of new climate technologies.

4.2. Normality of residuals

Table 1 presents descriptive statistics for residuals of four elements of the Kaya identity: carbon intensity (CE), energy intensity (EG), GDP per capita (GP), and population (P). The table shows the mean (Mean), standard

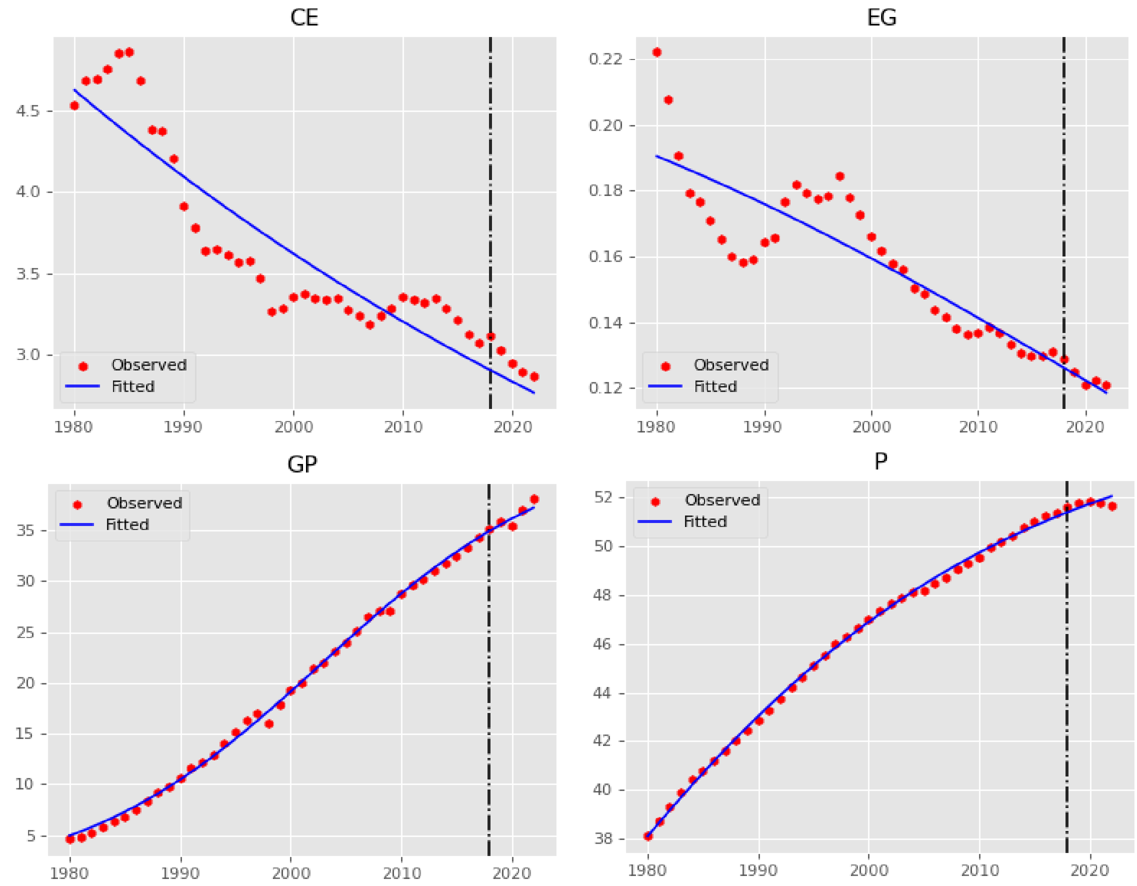


Figure 1. Observed value vs. Fitted value.

Note: The figure shows observed values and fitted values for each element of the Kaya identity: carbon intensity (CE), energy intensity (EG), GDP per capita (GP), and population (P). The red dots in the figure show observed values during 43 years (1980-2022). The blue line in the figure represents fitted values from the logistic function for the same period. The black dashed line indicates the year 2018, the peak of carbon emission in Korea.

deviation (SD), skewness (Skew), and kurtosis (Kurt) of residuals, as well as the Jarque and Bera (JB) normality statistics.[2] The test results show that each residual is normally distributed. The p-value represents the probability of obtaining the observed test statistic under the null hypothesis of normality. Since the p-value is higher than the significance level, we fail to reject the null hypothesis and conclude that the residual is normally distributed. This means that the error term can be assumed to follow a normal distribution holds.

Table 1 shows the correlations between the residuals generated when estimating the trends of the four factors. We see that there is a negative correlation between carbon intensity and energy intensity. It means that while the trends in the two technology factors are decreasing, the noise around them tends to move in an opposite direction. In other words, a temporary decrease in carbon intensity is likely to be accompanied by a temporary increase in energy intensity. This feature may help policymakers formulate a climate policy to induce a simultaneous decrease in both factors through the introduction of new climate technologies.

4.3. Probability of achieving the NDC target

Panel A of Figure 2 compares the predicted pathway with the NDC target pathway up to 2030, the target year. The figure shows that carbon emissions peaked in 2018, declined during the pandemic era, and then rebounded

[2] We use Fisher's definition of kurtosis, and thus the kurtosis of a normal distribution is zero.

Table 1. Descriptive statistics and normality test of residuals.

Variable	Mean	SD	Skew	Kurt	JB-statistic	p-value
CE	0.002	0.236	0.026	-0.918	1.514	0.469
EG	0.000	0.011	0.413	0.748	2.227	0.328
GP	-0.008	0.398	-0.133	0.385	0.483	0.785
P	0.000	0.141	-0.446	-0.062	1.764	0.414

Note: The table presents descriptive statistics for residuals of four elements of the Kaya identity: carbon intensity (CE), energy intensity (EG), GDP per capita (GP), and population (P). The table shows the mean (Mean), standard deviation (SD), skewness (Skew), and kurtosis (Kurt) of residuals. We use Fisher's definition of kurtosis, and thus the kurtosis of a normal distribution is zero. The table also presents the Jarque and Bera (JB) normality. The p-value represents the probability of obtaining the observed test statistic under the null hypothesis of normality. We retrieve data from the ECOS of the Bank of Korea and KOSIS of Statistics Korea, ranging from 1980 through 2022.

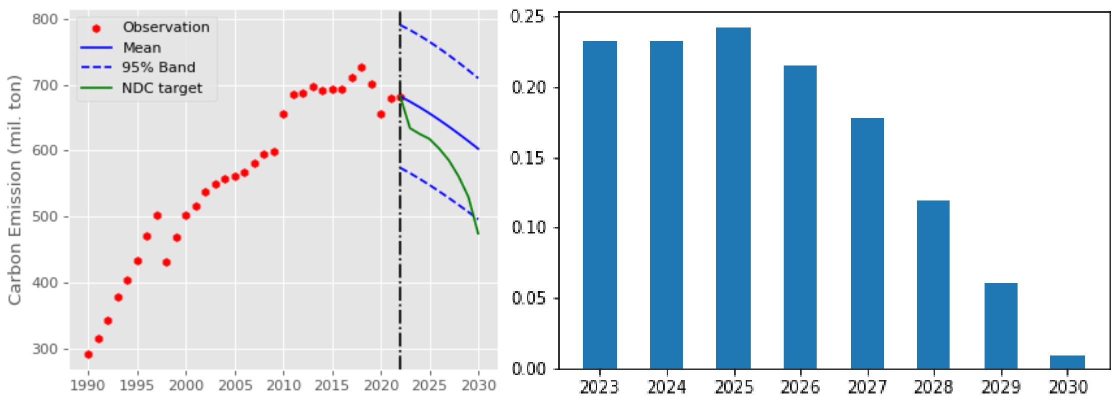
Table 2. Correlation between residuals.

	CE	EG	GP	P
CE	1.000			
EG	-0.508	1.000		
GP	-0.371	0.118	1.000	
P	0.270	0.222	-0.378	1.000

Note: The table shows the correlation between residuals of four elements of the Kaya identity: carbon intensity (CE), energy intensity (EG), GDP per capita (GP), and population (P). Residuals are generated when estimating Equation (3).

when the pandemic ends. Based on the analysis in this study, it is estimated that the trend will continue to decline from 2023 to 2030. Notably, the estimated pathway remains above the NDC target pathway and continues through 2030. This means that the probability of meeting the NDC target is not high when assuming that the observed trends in the components of the Kaya identity (population, per capita income, energy intensity, and carbon intensity) up to 2022 continue through 2030. Given that the NDC target pathway falls outside the 95% prediction band in 2030, the NDC target would not be met unless significant improvements in climate technology are made before that point.

Using the previous result that emissions projections follow a normal distribution, there is less than a 0.1% chance of meeting the NDC target by 2030. Panel B of Figure 2 shows the trajectory of the probability of meeting the NDC target over the period from 2023 to 2030. We see a slight increase in the probability of achievement from 23.3% in 2023 to 24.2% in 2025, followed by a steady decline over time. This shows that the adoption speed of new climate technology is not fast enough to achieve the final NDC goal in 2030.



Panel A. Predicted pathway until 2030. Panel B. Probability of meeting the NDC target.

Figure 2. Predicted pathway vs. NDC target pathway.

Note: The figure compares the predicted pathway with the NDC target pathway. The red dots in the figure show observed values of carbon emission in million tons during 33 years (1990-2022). The blue line in the figure represents the mean path *predicted by using the Kaya identity for the same period. The blue dashed lines are the prediction band at the 95% confidence level. The green line shows the NDC target path announced by the Korean government. The black dashed line indicates the year 2022, the last realized observation.*

4.4. Required improvement of climate technology

The Kaya identity expresses carbon emissions as the product of four factors: population, per capita GDP, energy intensity, and carbon intensity. Given two other factors fixed, carbon intensity has the inverse relation with energy intensity within the Kaya framework. It means that a decrease in one factor can coevolve with an increase in the other factor and vice versa. Similarly, a reduction in energy intensity will only lead to a reduction in carbon emissions if the reduction in energy intensity is greater than the temporarily paralleled increase in carbon intensity. The converse direction also holds. Therefore, the inverse relation highlights the importance of considering both factors simultaneously when addressing climate change mitigation. A comprehensive approach that targets both energy efficiency and carbon reduction is necessary to achieve the NDC target.

Figure 3 shows the inverse correlation between energy intensity and carbon intensity, two proxy indicators of climate technology, within the Kaya framework. Each inverse curve in the figure shows the level of climate technology required to achieve the NDC target, given the population and GDP per capita levels in a given year. Curves for the next eight years (2023-2030) are shown in the figure, including 2022. It can be seen that the curve for each year gradually shifts downward as the NDC targets increase over the period from 2022 to 2030. The result suggests that energy intensity and carbon intensity are interrelated so it is important to understand the impact of enhancement of climate technology. The improvement of climate technology contributes to reducing both energy intensity and carbon intensity while increasing the output. Over time, investing in climate technologies can help to further reduce both energy and carbon intensity and mitigate the impacts of climate change.

This analysis does not identify the technologies needed to achieve the required emissions reduction, which may involve identifying new technologies or improving existing ones. In practice, it is important to identify the required technologies that include renewable energy technologies, energy efficiency improvements, carbon capture and storage, and other innovations. This can be done by analyzing the technical specifications of the technologies and identifying the level of improvement needed to achieve the required emissions reduction. It is also a significant task to develop a roadmap for implementation. A roadmap for implementation can be developed, outlining the steps needed to achieve the required improvement in climate technology. This roadmap may include research and development, pilot projects, and scaling up of the technologies, as well as policies and incentives to encourage adoption and investment in the new technologies.

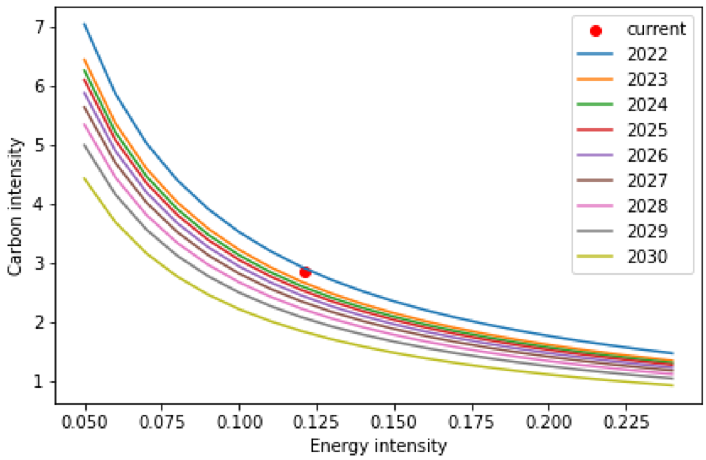


Figure 3. Implication for climate technology: energy intensity & carbon intensity.

Note: This figure shows the inverse correlation between energy intensity and carbon intensity, two proxy indicators of climate technology. Each curve in the figure shows the level of climate technology required to achieve the NDC target, given the population and GDP per capita levels in a given year. Curves for the next eight years (2023-2030) are shown in the figure, including 2022. The red point on the curve corresponding to 2022 represents the last observed level of energy intensity and carbon intensity. It can be seen that the curve for each year gradually shifts downward as the NDC targets increase over the period from 2022 to 2030.

5. Discussion

5.1. Interpretation of the results

The prediction based on our model shows that the Republic of Korea faces a significant risk of failing the NDC target. This finding is consistent with previous studies. Dong et al. (2018) use the methods of trend extrapolation and back propagation neural networks and show that there will be a shortfall in achieving targets by South Korea. den Elzen et al. (2019) present the evaluation results on whether G20 members are on track to meet their NDCs. In their evaluation, the Republic of Korea needs a high additional effort (the current policy trajectory is more than 15% above the unconditional NDC target). The evaluation is based on the information available until 2018, such as NDC and policy scenario published by the Korean government as well as three independent sources (the Climate Action Tracker, Joint Research Centre, PBL Netherlands Environmental Assessment Agency).

Our assessment, on the other hand, utilizes the latest information on the 2021 revised NDC and the current government's energy policy, which has begun since 2022. As a result, South Korea's carbon emissions in our analysis are expected to follow a path of continuous decline through 2030, with some acceleration in the rate of decline. This result differs from the results of den Elzen et al. (2019), which predicted that South Korea's carbon emissions will continue to increase until 2030.

This result of CO-STIRPAT should be read with caution since it shares the caveats addressed in den Elzen et al. (2019). First, it does not mean that a country currently on track to achieve its NDC is undertaking more mitigation action than a country not yet on track. It is because the level of effort to implement NDCs depends highly on the ambition level as well as the strength of the current policies. Note that our model does not assess the ambition level directly although the prediction model is flexible enough to be amended to incorporate the factor. It is also important to consider that NDCs are inherently heterogeneous since they are determined on a country-by-country basis.

Second, any projected pathway is subject to the uncertainty associated with the policy impact as well as other factors (population, per capita GDP, and technology developments). Although the policy scenario used in this study accounts for the latest information at least through 2022, there exists uncertainty around the implementation gap. Since Korea pledges something above what it has achieved, it would take years to close the gap by strengthening the implementation of newly designed policies.

5.2. Research contribution and limitation

A novel aspect of CO-STIRPAT is that the prediction model is so straightforward that it can be modified easily to accommodate uncertain factors to assess the likelihood of fulfilling the NDC target of individual countries. Any projection is subject to the uncertainty associated with ImPACT factors: population, per capita GDP, energy efficiency, and carbon intensity. Rogelj et al. (2017) systematically explore possible interpretations of NDC assumptions, to understand the origin of emission uncertainties. They show that this uncertainty has critical implications for the feasibility and cost to limit warming well below 2 °C and further to 1.5 °C. While the traditional STIRPAT model uses only one uncertainty factor, our model specifies separate sources for all uncertain drivers of carbon emissions within the ImPACT identity. And whenever it is needed to consider additional factors depending on the purpose of the analysis, the model can be flexibly modified to include associated uncertainties by adding error terms for those factors.

Liu and Raftery (2021) provide fully statistically-based probabilistic forecasts of the main drivers of future global carbon emissions and the resulting global temperature change, taking into account the associated uncertainty. Their analysis based on a joint Bayesian hierarchical model reports that both the central forecasts and the assessment of uncertainty are satisfactory. This provides a comprehensive tool to give statistical assessments of whether countries are on track to meet their NDC, coupled with the associated uncertainty. Compared with the large-scale model that focuses on global carbon emissions and temperature for many countries, our model is a small-scale model that can serve as a more concise tool to predict the emissions of each country. Although it is less comprehensive, our small-scale model may be more tractable when it is necessary to customize the model to account for the specificities of individual countries. For example, Dong et al. (2018) show that there is no common trend that can be used as a suitable benchmark for every country for the implementation of carbon reduction targets of the Paris Agreement and their INDC goals.

In addition, our small scale CO-STIRPAT can be easily customized to consider the nonlinear behavior of the ImPACT systems over time. The framework provides a method to understand the dynamic behavior of the ImPACT (IPAT, or STIRPAT) systems. It is based on the recognition that the behavior of the whole cannot be explained in terms of the behavior of the parts. However, the current version is designed to account for interactions between factors through correlations between error terms. This approach is not sufficient to fully accommodate the interaction dynamics, as the non-linear trend of each factor is set to be deterministic over time. In future research, the model could be improved to allow for more sophisticated interactions between the trend terms. It would aim to capture properties of the whole that cannot be found among the properties of the elements. In that spirit, it would be interesting to explore machine learning models (back propagation neural networks, support vector machines, long short-term memory neural networks, random forests, and extreme learning machines) reviewed by (Zhao et al. 2023).

Along with climate technology and climate policy, the potential size of climate finance can affect the likelihood of achieving the NDCs. It is essential to estimate how quickly private climate finance would be scaled up, which we have not adequately addressed in this paper. In this regard, we suggest paying attention to the possibility that private climate finance can be scaled up by linking it to ESG investments. Considering that climate risk is a systemic ESG risk, ESG investment is likely to coevolve with climate finance.[3]

5.3. Implication for climate policy

The finding carries practical implications for the future discussion of climate policy. Several policy options can be considered concerning the effectiveness, ambition, and feasibility of current climate policies and measures.

On the one hand, regarding effectiveness, a country may need to implement more aggressive climate policies to increase the probability of meeting its target. Such policies include carbon pricing, renewable energy incentives, and energy efficiency measures. The most effective way to cope with failing the NDC target is to take action as soon as possible to implement more effective climate policies and work towards achieving the long-term goal of net-zero emissions.

On the other hand, regarding ambition, a country may need to reevaluate the level of ambition of its target to ensure that it is aligned with the latest economic conditions. A high probability of failing the NDC target may indicate that a form of greenwashing has occurred, whereby overly ambitious targets are set based on strategic or

3 For the detailed discussion on systematic ESG risk, strategic screening strategy, how it is related to passive investing, and extended criteria for optimal portfolio, please refer to Jin (2018, 2022a, 2022b, 2022c) and Kim, Son, and Jin (2022).

opportunistic motivations. If this is the case, efforts to increase accountability and transparency will be needed to curb the occurrence of greenwashing. It is important to ensure that countries are transparent about their emissions and progress towards meeting their NDC targets. Robust reporting and monitoring systems can help to hold countries accountable for meeting their commitments. From a strategic perspective, carbon border adjustments can help to address carbon leakage and ensure a level playing field for businesses in countries with ambitious climate policies. This policy involves imposing a carbon price on imported goods based on their carbon footprint, which can encourage countries to adopt more ambitious climate policies.

Regarding feasibility, efforts are requested to increase the feasibility of the overall climate policy through various aspects. International cooperation can help countries meet their NDC targets by providing financial and technical support. Developed countries can provide financial and technological assistance to developing countries to help them transition to low-carbon economies. As another option, carbon offsetting involves purchasing carbon credits from projects that reduce carbon emissions to compensate for emissions that cannot be reduced domestically. This can help a country meet its NDC target by offsetting emissions that are difficult or costly to reduce. Its impact on carbon emissions can be incorporated easily into CO-STIRPAT.

6. Conclusion

This paper proposes a framework for estimating carbon emissions from four elements of the Kaya identity: population, GDP per capita, energy intensity, and carbon intensity. The methodology helps to identify the probability of achieving the NDC targets, assuming that the trends in the four factors will continue in the future. This approach also allows us to explicitly verify that, given exogenous trends in population growth and economic growth, there is an inverse relationship between energy intensity and carbon intensity. Furthermore, advances in climate technology are essential to increase the likelihood of meeting the 2030 NDC target without straining economic growth. This can have implications for the direction of climate policy concerning whether to focus more on improving energy intensity or carbon intensity.

Our CO-STIRPAT approach is highly feasible and provides a simple and intuitive framework to conduct an empirical analysis of strategies for achieving NDC targets. Empirical evidence from South Korean data suggests that meeting the 2030 NDC target will be quite challenging. This suggests that policymakers could benefit from incorporating this information into their policy-making process. Given the economic conditions in the period up to 2030, it is possible to examine strategies for reducing energy intensity and carbon intensity and, if necessary, focus on the more cost-effective of the two. Above all, efforts should be made to develop and early adopt new climate technologies related to both elements.

There are several directions for future research. An underlying premise of our analysis is that the Kaya identity accurately captures the main factors driving carbon emissions. Future research needs to validate this assumption by examining the impact of including other factors. Next, we conducted our analysis under the assumption that changes in indicators related to the Kaya identity converge to a stable level over time during our sample period. In future research, the approach can be improved to capture situations where the metric is changing unsteadily to apply a longer prediction horizon. Next, we found that the risk of non-compliance with NDC targets is not low when considering country-specific conditions, but this result may vary depending on the context of each country. Considering the finding of previous research (Dong et al. 2018) that there is no common trend that can be used as a suitable benchmark for every country, it will be important to refine the model to identify differentiated trends that can be used as appropriate benchmarks by each country.

Our analysis using CO-STIRPAT provides a rigorous description and intuitive interpretation of measuring the probability of meeting NDC targets. By utilizing the easily modifiable analytical tool presented in this paper, it would be possible to more accurately identify the country-specific conditions when designing climate policies and to explore strategic responses regarding how to effectively and efficiently close the existing gaps against NDC targets. We hope it is one step in a long process of improving our understanding of climate policy direction.

Funding Statement

This research received no external funding.

Acknowledgment

Acknowledgments to anonymous referees' comments and editor's effort.

Conflict of Interest

The author claims that the manuscript is entirely original, and declares no conflicts of interest

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